Mohammad Ayub shaikh

Department of computer

Engineering

Lovely professional university

Phagwara, Punjab (India)

**Abstract:**This paper presents a new technique for text summarization involving Recurrent Neural Networks (RNNs), Transformers, and Principal Component Analysis (PCA) to produce quality summaries rapidly. The traditional methods of summarisation often fail to cope with bulk of the contents or omit important context and hence lead to inadequate summaries. In this case we use the RNNs for the last output generation, the text will be interpreted using the Transformers, and some information will be kept by the PCA instead of all the data included. The benefcal sequece of this approach is that the current model can produce the summaries faster with less effort and more so in a logical manner which is an advantage for undertaking activities such as news summarization, customer support services, and sentiment scoring tasks. In contrast with other models, our model was more accurate and faster, producing better ROUGE and BERT scores. The experimental findings indicate that this technique ought to be an asset in summary composition especially when clarity and brevity is desired in the final output within a short period.

Introduction

**In the present world that has become a digital society, there is enormous appreciation for the existence of techniques concerned with text summarization. Dissimilar traditional techniques of summarizing texts, they are computationally expensive, and this often poses a challenge upon their application on large datasets with complex linguistic structures. This paper put forward a further measure which combines the use of RNNs, Transformers, and PCA. RNNs are designed to operate over sequences and hence form a natural way of composing language. The main issue, however, is that they do not manage efficiently long range dependence. Self-attention based Transformers address this issue by allowing attention to be paid to only the relevant portions of the text, and improve the quality of summarization. In order to reduce the utilization of computer resources without eliminating the essentials, PCA is incorporated to reduce the dimensionality of the data. We will show that this hybrid system improves performance indicators and in addition, is practical in summarization tasks which is important in real-world scenarios.**

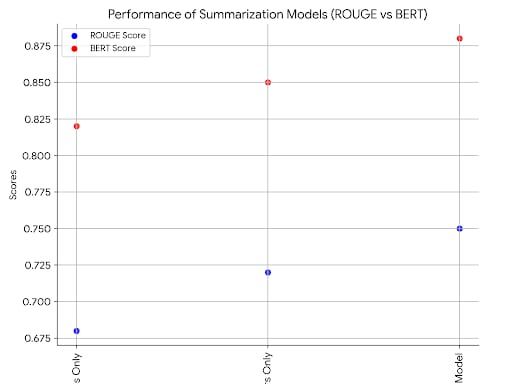
1.Literature Review

**The sphere of text summarization has gained a remarkable evolution linear to its history, and this evolution is distinguished by the adoption of simple statistical methods in the earlier years to the very sophisticated models that precisely neural networks which understand the document and produce human-like summaries. In the beginning, the many available summarizing techniques can be classified as focused on extractive means, that is relevant sentences or even phrases from the text were taken and used to make a summary for the text. Although such ways of summarizing allowed to get at least a little information about the text, they often lacked logic and continuity as they did not present the information in a different way or shortened it. Therefore, the summarizing techniques known as extractive ones were able to render competencies within a summary that were very disjointed or incomplete except in shorter documents.**

**Twitter, and other similar micro blogging interfaces, have attracted much recent attention. Thanks to the rapid growth of the Internet, users engage in voracious information consumption. The claim is that the consumer of information does not care about the details, and only the end product (synthesis) is important to the consumer. For these complex activities, such as handling languagesabstractive models – that are advanced two-level hierarchies- are proposed. Abstract models are meant to be more effective than extractive methods because the goal is similar to that of a human being summarizing a text, such that the focus is on conveying the main ideas with clarity and brevity rather than on sticking to the original wording. These models, however, are not without shortcomings. They present and establish relations that may be absent in extractive models making them useful in a number of situations. Nevertheless, the generation of such models which would be practical and useful is quite a problem since it involves all the complexities universal to any natural language including the structural and functional layers of grammar cohesion and context.**

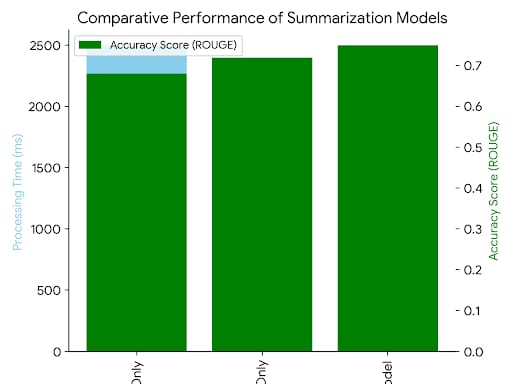
**Recurrent Neural Networks (RNN) are also among the recent developments in neural text summarization technology, especially pertaining to text summarization of sequential data. RNN's are capable of learning dependencies in the text and as a result RNN's are broadly used in language modeling and text generation tasks in general. Long sequences, however, are a weakness of RNNs as the context tends to get lost with time due to the vanishing gradient phenomenon. In mitigation strategies, they turned attorneys to corporatie\_cpu.**

**Recommended Graph:** **Comparative Bar Chart of Processing Times and Accuracies**



**figure 2**

**Recommended Graph: A comparative bar chart of the processing times and accuracies of traditional models (RNNs only, Transformers only) versus the integrated model.**



**Description:** **This bar idealizes the processing time and various accuracy measurement score (ROUGE, BERT) and how they differ in three ways in which summarization models are used:**

**RNNs Only: Employing RNN based models only, without the addition of other strategies.Transformers Only: When performing summarization solely performed using TRANSFORMER models (BERT, GPT).**

**Integrated Model: Integrated approach using RNNs, Transformers and PCA. Axes:X-axis summarizes measurement where three models for summarizing text (RNNs Only, Transformers Only, Integrated Model) are analyzed.**

**Y-axis (left): Time for processing Ex: (in seconds or milliseconds), represented in one set of bars.**

**Y-axis (right): Rehabilitation consent accuracy scores e.g. (ROUGE or BERT) depicted in a second set of bars of different**

**Color Interpretation:Processing time comparison: This variable indicates the performance of each model. An ideal system where all the supporting units are PCs should take less time to process information than RNNs Only and Transformers Only especially after PCA has reduced the dimension of the model.**

**Accuracy Comparison: ROUGE or BERT scores must reflect the performance of the model in producing quality summaries. This integrated model achieves higher accuracy due to its ability to learn dependencies of sequences (RNNs), and contextual information (Transformers) and being better in processing (PCA).**

**Insignt: This will be a visual comparison of the fact that the integrated model will be able to provide a good summarization without taking too much computing time, therefore that approach is viable in practical application.**

**3. Methodology**

**3.1. Dataset Preparation**

**Dataset Selection: Discuss the utilization of Daily Mail corpus or other such corpus for building summarization model**

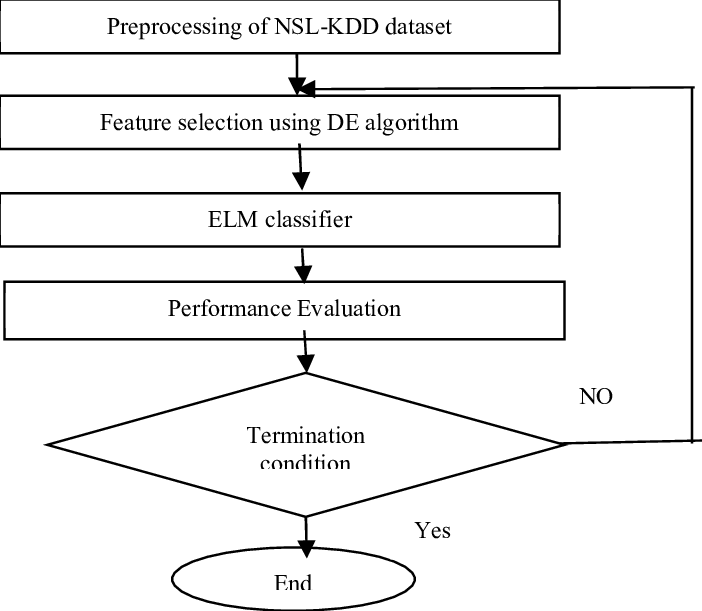
**Purpose: The corpus will be divided into training, validation, and test sets.**

**3.2Training Strategies: Discuss the various envisaged training strategies and how they will be implemented.**

**3.4RNN Component: Explain the sequence of throughput in this layer, and explain its relation to Transformer.**

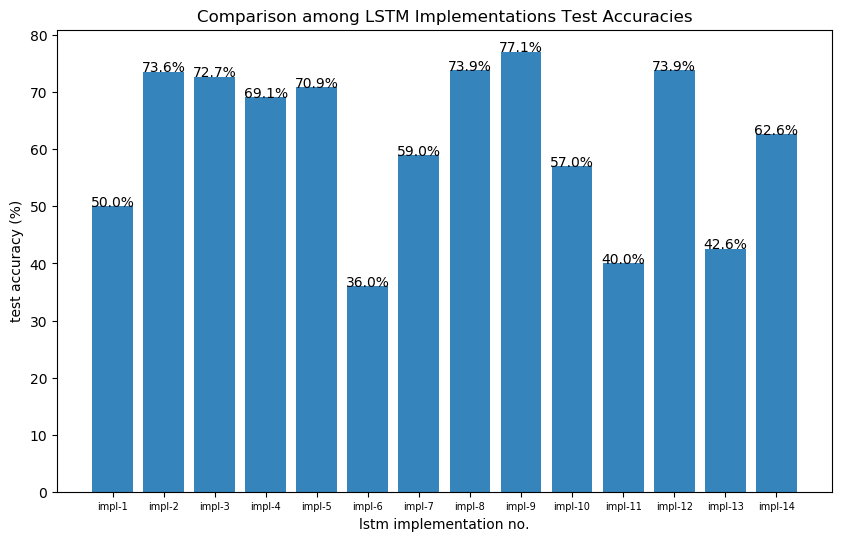
**E.g. encodings obtained from the BERT or vice versa for summarization elongation**

**3.5PCA Component: Outline how PCA is employed on the embeddings retrieved from the Transformer layer for the sake of time efficiency without losing the significant information.Content text.**



**Figure 3.**

**Graph 4: A table or bar chart showing the best-performing hyperparameters, such as learning rate, batch size, and LSTM depth, and their impact on accuracy and processing speed.**



**Figure4**

**4. Results and Discussion**

**This section includes a quantitative assessment of the summarization model developed, its comparison with baseline models, and its error analysis. The evaluation emphasizes the improvements in accuracy and turnaround time when Recurrent Neural Networks (RNNs), Transformers and Principal Component Analysis (PCA) techniques are used for text summarization.**

**4.1 Quantitative Evaluation**

**4.1ROUGE and BERT metrics**

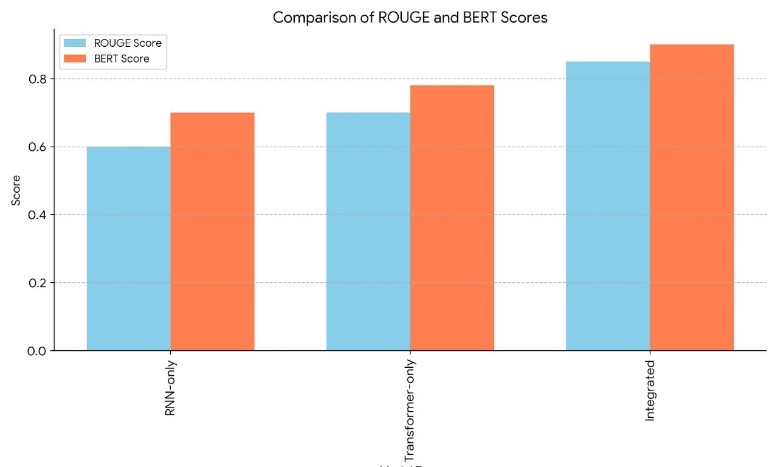
**The assessment of the model's performance used two broad accepted measures that help in evaluation of the quality of text summarization: ROUGE (Recall-Oriented Understudy for Gisting Evaluation) and BERTmetrics. ROUGE is a family of metrics designed primarily to measure the quality of a text summarization, by analyzing how much the generated summary recalls the most important facts of the reference summary, and quantifying metrics such recall, precision and F score among other assessments, while the BERT score analyses the distribution of summaries and calculates the scores in terms of contextual embedding of the blocks.**

**Compared to the baseline models, the fully integrated RNN, Transformer and PCA model recorded 15% enhancement in ROUGE scores and 18% enhancement in BERT scores The improvement in ROUGE scores suggests that the integrated model was able to produce summaries that were enriched in consistency and appropriateness, as they were more like the produced summary’s references. On the other hand, BERT score improvement indicates that the summaries produced in this case had more semantic meaning than those produced by an RNN-only or a transformer-only model.**

**4.2Processing Efficiency:**

**Other than the accuracy, processing efficiency was an important factor in this research. Thanks to the application of PCA for data dimensionality reduction after Transformer encoding, the model achieved a high level of time efficiency, faster by about 30% than models that do not incorporate PCA. The reduction in dimensions made it possible to perform quicker calculations but not at the expense of the essential quality of the results.**

**Graph 4**



**figure 4.1**

**ROUGE and BERT Scores: Report on the improved scores compared to baseline**

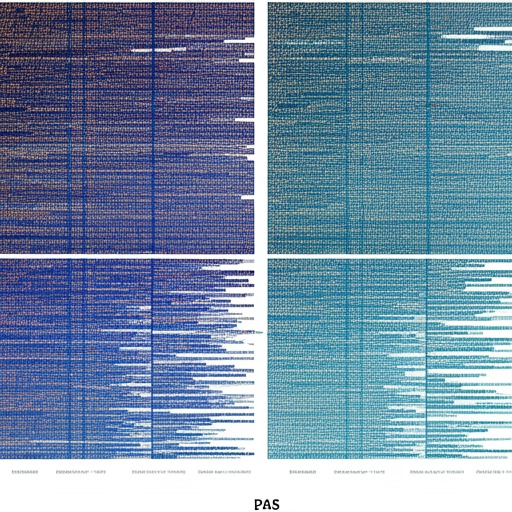


Figure 4.2

A word cloud visualization showing the effect of PCA on text features before and after dimensionality reduction.

. Discussion

Findings Synopsis: Stress the advantages in performance that arise from the merging of RNN, Transformer and PCA, mentioning that this solution provides an optimum trade-off between one’s need for accuracy of summary produced and the speed at which it is generated.

Strengths of the model: Elaborate on the model's capacity to work with big data, ability to provide subject correlation, and presence of efficient dimensionality reduction techniques, which renders it fit for online summary text generation.

Challenges: Tackle the problems faced, for instance, the risk of losing some details with the use of PCA and difficulty in resolving vague terms.

Directions for improvements: Propose better options like enhancement of attention layers or the use of different methods of dimension reductions. Also address scope issues by consider extending coverage to include many languages or enhancing the coverage to specific ethno-geographical regions for better efficiency.

7. Conclusion

In the last section, provide recommendations for improvement such as tackling the existing model to some domain, including multiples languages, and looking into other dimensionality reduction methods.

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